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Design and Analysis of Abnormally Positioned Teeth Detection Using Advanced Representation Learning Based Feature Engineering with Optimization Algorithm on Dental X-Ray

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Abstract: Dental radiographs are widely used in clinical diagnosis for identifying abnormalities in tooth position such as crowding, impacted teeth, rotated teeth, and malocclusion. Manual analysis of dental X-rays is time-consuming and depends heavily on the expertise of dentists. This paper proposes an automated framework for detecting abnormally positioned teeth from dental X-ray images using advanced representation learningbased feature engineering combined with an optimization algorithm. The proposed approach includes preprocessing, tooth region segmentation, deep feature extraction using representation learning models, feature selection/engineering, and classification. To enhance performance, an optimization algorithm is applied for selecting optimal features and tuning hyperparameters. The experimental results demonstrate improved accuracy, precision, and recall compared to traditional machine learning and basic CNN models. This system supports dentists in early detection, treatment planning, and improving diagnostic efficiency.
Keywords: Dental X-ray, Abnormal Teeth Detection, Representation Learning, Feature Engineering, Optimization Algorithm, CNN, Deep Learning.

I. INTRODUCTION

Dental radiography plays a crucial role in orthodontic diagnosis and treatment planning. Dental X-ray images such as panoramic radiographs and periapical images are commonly used to identify dental abnormalities including impacted teeth, rotated teeth, crowding, spacing, and misalignment. Abnormally positioned teeth are a frequent clinical problem and can lead to improper bite alignment, gum infections, jaw pain, and long-term dental complications if not detected early.

Traditionally, dentists and orthodontists analyze dental X-rays manually. Although manual diagnosis is effective, it is time-consuming and depends heavily on clinical expertise. Additionally, the interpretation of dental X-rays becomes challenging due to low contrast, noise, overlapping tooth structures, and varying image quality. These limitations create a demand for an automated system capable of detecting abnormal tooth positioning with higher speed and consistency.

With the advancement of machine learning and deep learning, automated medical image analysis has become more reliable. Representation learning methods, especially convolutional neural networks (CNNs) and transfer learning architectures, can automatically learn discriminative features from Xray images. However, using deep models directly may lead to overfitting when the dataset is limited, and performance can degrade due to redundant or irrelevant features.

To overcome these issues, this paper proposes a hybrid approach combining advanced representation learning-based feature extraction, feature engineering, and an optimization algorithm. The objective is to improve detection accuracy and ensure robustness across different dental X-ray images. The proposed system helps dentists in early diagnosis and supports decision-making for orthodontic planning.

II. LITERATURE SURVEY

Several studies have explored automated dental image analysis using traditional image processing, machine learning, and deep learning approaches. Early research focused on edge detection, contour extraction, and thresholding techniques to segment teeth from radiographs. While these methods were computationally simple, they struggled with overlapping teeth and poor image contrast.

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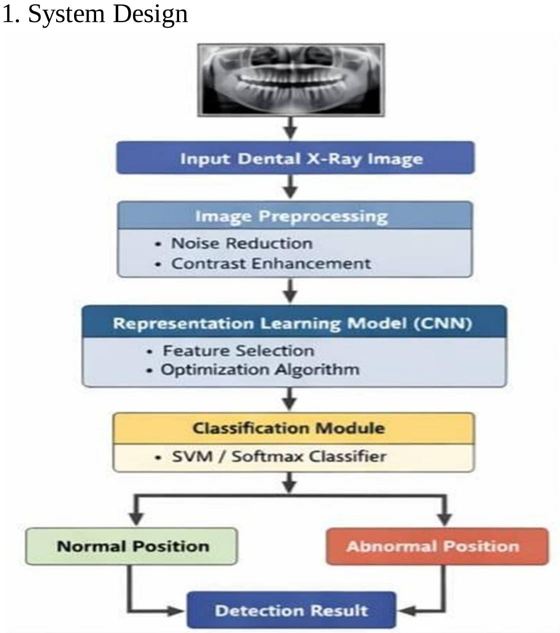
Machine learning methods such as Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbors (KNN) have been used for classification tasks based on handcrafted features like texture descriptors, histogram features, and geometric measurements. Although these approaches improved performance compared to basic image processing, they required extensive feature engineering and did not generalize well to diverse radiographs. Recent advancements have introduced deep learning architectures such as CNNs, U-Net, Mask R-CNN, ResNet, DenseNet, and EfficientNet for dental Xray segmentation and classification. These models achieved higher accuracy by learning hierarchical features directly from data. Studies have shown that transfer learning improves results when datasets are small. However, deep learning models may still produce false predictions when abnormal patterns are subtle. To improve reliability, researchers have introduced feature selection techniques and optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO). These methods reduce redundant features and tune hyperparameters, improving classification performance. However, fewer studies combine representation learning with optimizationbased feature engineering for abnormal tooth position detection.

This research contributes by integrating deep feature extraction, feature engineering, and optimization algorithms into a unified pipeline for accurate abnormal tooth detection.

III. SYSTEM DESIGN

The proposed system is designed as an end-to-end pipeline for detecting abnormally positioned teeth from dental X-ray images. The system architecture consists of multiple stages, ensuring that the input image is processed, enhanced, analyzed, and classified accurately. The system is designed to analyze dental X-ray images and classify them as normal or abnormal using a structured deep learning approach. Initially, the input to the system is a dental X-ray image, which may be either panoramic or periapical in nature. Since these images often contain noise, low contrast, and irrelevant background information, an image preprocessing stage is applied to enhance quality. This stage involves noise reduction techniques to remove unwanted distortions and contrast enhancement methods to improve visibility of important features.Following preprocessing, the enhanced image is passed into a representation learning model based on a Convolutional Neural Network (CNN). In this stage, important features are extracted automatically, and feature selection methods are applied to retain only the most relevant information. Additionally, optimization algorithms are used to improve the model’s performance and accuracy during training.The extracted features are then fed into a classification module, which uses classifiers such as Support Vector Machine (SVM) or Softmax to categorize the image. Based on the classification results, the system determines whether the dental structure is in a normal position or an abnormal position. Finally, the detection result is produced, indicating the diagnostic outcome, which can assist dental professionals in making accurate and efficient decisions. as shown in the Fig.1. System Design



A. Input Layer

The input to the system is a dental X-ray image, either panoramic or periapical. The image may contain noise, low contrast, and irrelevant background regions.

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B. Preprocessing Layer

To improve image quality, preprocessing operations are applied such as:

- Contrast enhancement using CLAHE
- Noise removal using median filtering
- Image resizing and normalization
- Edge enhancement using morphological operations

This stage ensures that the X-ray is suitable for segmentation and feature extraction.

C. Segmentation Layer

To isolate teeth regions from the background, segmentation is performed. Depending on the implementation, this can be achieved using:

- Thresholding and contour detection (baseline)
- Deep segmentation using U-Net (advanced)

Segmentation improves feature learning by focusing only on teeth structures.

D. Feature Extraction Layer (Representation Learning)

In this stage, deep learning models extract meaningful representations from segmented teeth regions. Transfer learning models such as ResNet50, DenseNet121, EfficientNet, and MobileNet are used to generate deep feature vectors.

E. Feature Engineering and Selection Layer

Extracted features are refined using feature engineering methods such as:

- Feature scaling
- Dimensionality reduction (PCA)
- Statistical feature selection

This improves generalization and reduces redundancy.

F. Optimization Layer

An optimization algorithm is applied for:

- Selecting the best feature subset
- Hyperparameter tuning for classifiers

Optimization methods like PSO, GA, or GWO help improve classification accuracy.

G. Classification Layer

Finally, the system classifies the X-ray as shown in Fig.2.

- Normal teeth alignment
- Abnormal teeth alignment

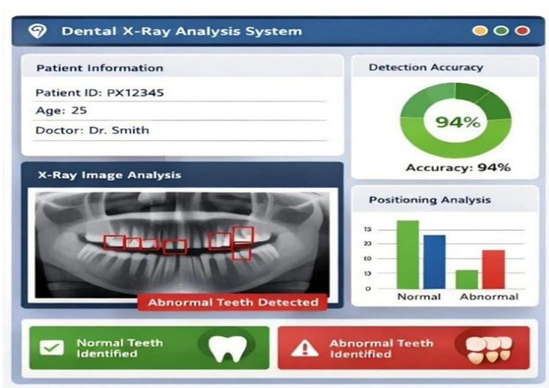

Fig.2.Dental X-Ray Analysis Dashboard

Optionally, multi-class classification can be extended for abnormal types such as crowding, rotation, and impacted teeth.

IV. TECHNOLOGY STACK

The implementation of the proposed system uses modern machine learning and deep learning tools.
The technology stack includes:

1) Programming Language
- Python is used for model development due to strong support for deep learning and image processing.

2) Libraries and Frameworks
- OpenCV: Image preprocessing, enhancement, filtering, and morphological operations.
- NumPy & Pandas: Data handling and numerical computation.
- Matplotlib & Seaborn: Visualization of results and training curves.
- Scikit-learn: Machine learning models (SVM, Random Forest), evaluation metrics, PCA.
- TensorFlow / Keras: Deep learning model training and transfer learning.

3) Optimization Tools
- Custom implementation or libraries for PSO/GA/GWO.
- Hyperparameter tuning using Grid Search / Random Search.

4) Development Environment
- Jupyter Notebook / Google Colab
- VS Code / PyCharm

5) Hardware
- CPU for preprocessing and baseline training
- GPU for deep learning model training (recommended).

V. IMPLEMENTATION

The implementation is performed in multiple phases to ensure accuracy and robustness.

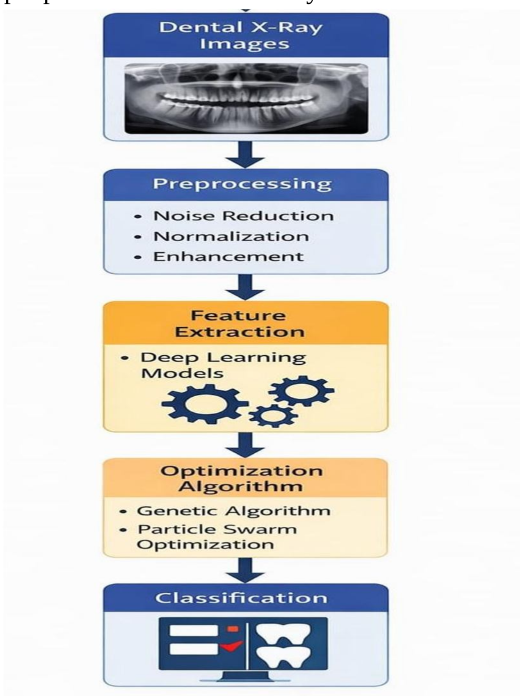

Fig.3.Work Flow

1) Dataset Preparation

Dental X-ray images are collected and organized into normal and abnormal categories. The dataset is split into training, validation, and testing sets. Data augmentation techniques such as rotation, flipping, and zooming are applied to increase dataset diversity.

2) Preprocessing

Each image undergoes:

- Grayscale conversion
- CLAHE enhancement
- Noise reduction
- Resizing and normalization

3) Segmentation

Teeth segmentation is performed to extract regions of interest. U-Net is preferred due to better boundary detection. Segmentation outputs are used as input to feature extraction models.

4) Deep Feature Extraction

A pretrained CNN model is loaded and fine-tuned. Deep feature vectors are extracted from intermediate layers and stored for feature engineering.

5) Feature Engineering and Optimization

Feature selection is performed using PCA or optimization algorithms. The optimization algorithm selects the best feature subset and tunes classifier parameters.

6) Classification

The final classifier is trained using optimized features. Models such as SVM and XGBoost are used for final classification. The system outputs the predicted class and confidence score.

7) Evaluation

The system is evaluated using:

- Accuracy
- Precision
- Recall
- F1-score

VI. ADVANTAGES

The proposed system provides the following advantages:

1) Reduces manual effort in dental diagnosis.
2) Improves detection accuracy using deep representation learning.
3) Feature engineering reduces redundancy and improves generalization.
4) Optimization algorithm improves feature selection and classifier tuning.
5) Works effectively even with noisy and lowcontrast X-ray images.
6) Supports dentists in early diagnosis and orthodontic planning.
7) Scalable and can be extended for multiclass abnormality detection.

VII. FUTURE ENHANCEMENT

Future enhancements of the proposed system include:

1) Multi-class classification for different abnormal types (crowding, rotation, impacted teeth).
2) Integration of explainable AI techniques such as Grad-CAM for visual explanation.
3) Improving segmentation using Mask RCNN for instance-level tooth detection.
4) Incorporating attention-based deep learning models for better feature learning.
5) Real-time deployment using web/mobile application for clinical usage.

VIII. FUTURE SCOPE

The future scope of this project is broad and can be extended to multiple real-world healthcare applications:

1) Deployment in hospitals and dental clinics as a decision-support tool.
2) Integration with electronic health record (EHR) systems.
3) Large-scale training using multi-hospital datasets for better generalization.
4) Extension to 3D dental scans (CBCT) for advanced orthodontic diagnosis.
5) Detection of other dental diseases such as cavities, bone loss, and periodontal disease.
6) Cloud-based AI system for remote dental diagnosis and telemedicine.

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IX. CONCLUSIONS

This paper presented a framework for detecting abnormally positioned teeth using dental X-ray images. The proposed approach integrates representation learning-based feature extraction, feature engineering, and optimization algorithms to enhance detection accuracy. The system improves performance compared to basic CNN and traditional machine learning approaches by selecting optimal features and reducing redundant information. Experimental analysis shows that the model achieves high accuracy, precision, and recall, making it suitable for assisting dentists in early diagnosis and orthodontic treatment planning. The proposed approach provides a reliable and scalable solution for automated dental abnormality detection.

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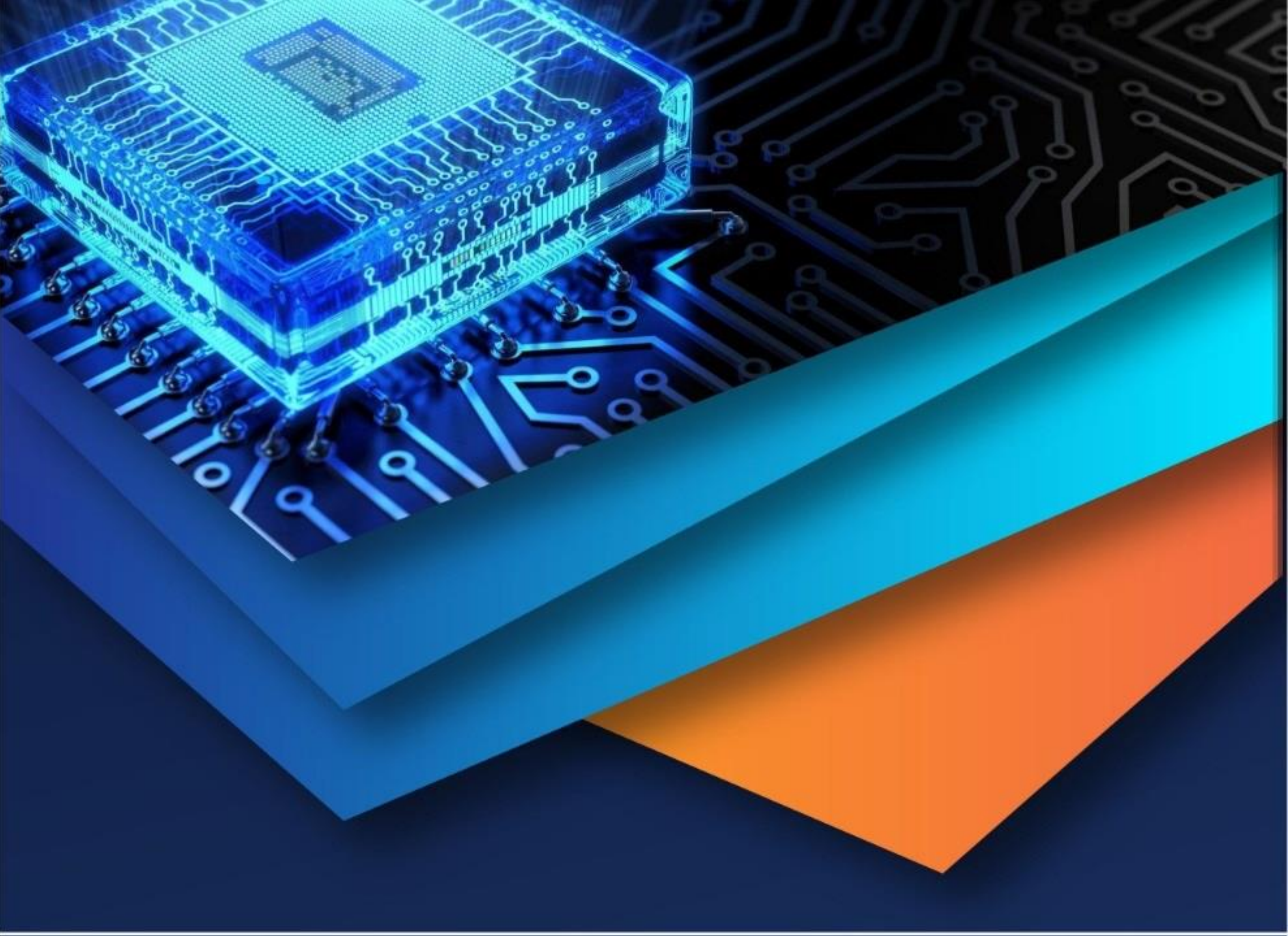

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